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Design and Planning of Closed-Loop Supply Chains: A Risk-Averse Multistage Stochastic Approach

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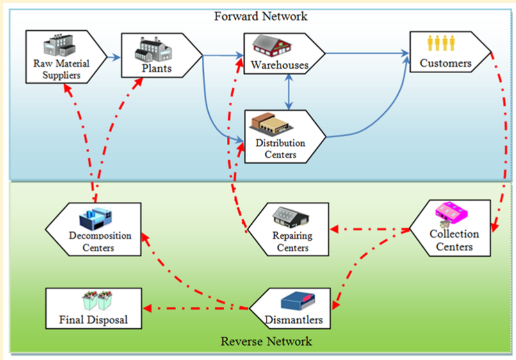
Supporting Information

ABSTRACT: This paper presents a comprehensive risk-averse multistage model for dealing with the design and planning problem of a closed-loop supply chain (CLSC) considering adjustments in the supply chain structure during the planning horizon as well as uncertainty in supply and customer demands. The stochastic approach addresses a problem of a generic multiperiod multiproduct CLSC with a general network structure of ten types of entities, risk-averse objectives associated with both costs and revenues, a flexible network structure, transport capacity, salvage grade of returned products, CO_2 emissions of the transport system, as well as minimum and maximum storage and processing capacity limits for network entities. A key aspect of the proposed work is to cope with a multiobjective function where the maximization of the expected profit is combined with the fundamental idea of risk management incorporated through the explicit trade-off between risk associated with costs and revenues. To the authors' knowledge, the joining of the considerations of risk management and aspects related to the opening/closing of entities during the planning horizon in a multistage stochastic context has not yet been considered. With the objective of achieving more reliable solutions, five objective functions that include risk-averse criteria are considered. A sensitivity analysis of the approach performance considering changes in the parameters associated with the risk metrics is conducted. Variations in the relevance of the risk quantification are carried out in order to show the trade-off between solution quality and handling of uncertainty.



1. INTRODUCTION

A closed-loop supply chain (CLSC) couples the traditional concept of a forward network with the reverse logistic processes where the path that follows products after being discarded by customers is explicitly considered.[1] The final aim of managing product recovery, remanufacturing, disassembly, and parts reusing with the flow of new products is to exploit the economic and environmental opportunities provided by this integration. The growing interest of researchers and practitioners in the joint study of forward and reverse networks has been recently observed to be justified by the need of dealing with the increasing shortage of natural resources, the necessity of reducing waste levels, and the emergence imposed by new government regulations.[2,3]

Closed-loop supply chains generally lead to more complex management problems than the traditional supply chains,[4] as they involve greater number of entities, flows of different types of products with different rates of recovery, and diverse material inventories. In addition, the coordinated management of such systems is strongly affected by the business environment volatility, and the need to account for uncertain parameters has been widely recognized as an increasingly important issue in supply chain and operations management research.[5,6,1] This increasing complexity requires decisions supporting tools to support the decision process that span from strategic to operational decisions.

In this context, the design problem of closed-loop supply chains is a strategic issue that requires informed decisions, as its effects will last for long periods, during which some parameters can vary due to the business environment. Considering an uncertain business environment where opening and closing network entities are a long and expensive process, inappropriate network entities selection is undesirable. Customers' demands, supply levels of raw material, as well as quantity and quality of returned products are critical parameters with quite uncertain values in such systems.

Given the previous mentioned issues, it is important to note that the use of stochastic programming techniques is unavoidable for CLSCs design and planning. In particular, the two-stage stochastic programming[7] appears as an appropriate form of modeling this uncertain environment where design decisions are considered as first stage variables and the planning variables are the second stage variables, which are based on the realization of the uncertain events. Nevertheless, most two-

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stage stochastic programming formulations consider expected costs/profits as the objective function. Formulations of this type are called risk-neutral approaches, because they consider the weighted average of relevant magnitudes of problems without paying explicit attention to particular uncertain events whose statistical characteristics differ from the expected values[8,9] and their occurrences can produce significant negative effects over particular magnitudes of the problems.

Risk-neutral formulations are not, however, the most adequate form of addressing CLSC problems, and risk-averse modeling approaches should be explored in order to search "immunized" solutions[10,11] against the possibility that, due to particular events not considered in the risk-neutral formulations, significant negative effects occur over certain magnitudes of the problems. CLSCs should be reliable with respect to certain events associated with the uncertain parameters in order to control their impact during the time horizon. Risk-averse approaches provide adequate solutions to such problems.[7] In these models the reliability of an optimization framework can be associated with the suitable selection of a utility function or risk measure, which can be incorporated into a given stochastic formulation as an objective function and/or constraints. The advantages of such models are both theoretical and practical.[12] To this end, it is worth noting that there is a big diversity of risk measures that show good characteristics in comparison with objective functions based on expected values. Three of the most employed measures in financial and management optimization problems are Value at risk (VaR), Conditional value at risk (CVaR), and Mean absolute deviation (MAD).[12−16]

MAD is a measure to overcome the computational weaknesses of variance where not only the negative deviations but also the positive deviations with respect to a mean point are penalized. VaR is used to quantify and control the worst expected loss over a given horizon under certain market conditions at a given level of confidence. CVaR, introduced by Rockafellar and Uryasev,[17] is similar to VaR; however, CVaR results by computing a weighted average between the value at risk and losses exceeding the value at risk. VaR, CVaR, and MAD have proved their advantages in financial areas and disaster management.[7,15] One of the most important features is that these measures have acceptable practical implementation. It is important to note that Rockafellar and Uryasev[17,18] showed that CVaR is superior to VaR in optimization applications. This conclusion is based on the analysis of different features of the measures, for example mathematical properties, stability of statistical estimation, and simplicity of optimization procedures.

In this paper, the problem of design and planning CLSCs under uncertainty is addressed with a multistage stochastic approach. The formulation proposed in this paper has a number of novel features. Adjustments in the network structure during the planning horizon are considered representing the dynamic nature of the closed-loop supply chain structure due to volatile market conditions adopting corrective choices in the planning period. The formulation determines an initial network configuration at the beginning of the planning horizon, which is effective for all uncertain conditions in the next periods, and it takes reparative operational and structural decisions in each time period, taking into account the uncertainty previously realized. To the best of our knowledge, the design problem considering a fix network structure determined at the beginning of the first time period and a flexible network structure at the start of subsequent periods has not been addressed in this manner in other multistage approaches. Furthermore, since the objective of the work is to avoid the profit risk given by the uncertain supply levels of raw material and customers' demands, five risk adversity measures are incorporated on the multistage framework. While two of the objective functions are based on the mean absolute deviation, the other three measures are centered on the conditional value at risk (CVaR) concept. So far, there is no previous research that includes, in a comprehensive way, the dynamic nature of the closed-loop supply chain structure and risk-averse metrics related to the network profit. In addition, in the formulation, the risks of costs and revenues are explicitly considered. With respect to other approaches, in this work the risk measures are applied separately to both revenues and costs in order to quantify the risks associated with the decreasing of revenues and increasing of costs. It is important to note that in the decision making procedure of the CLSC design and planning, in addition to considering the risk of profit, the trade-off between revenues and costs must be taken into account. Finally, this paper includes a comparative study of the proposed risk measures when the multistage stochastic approach is applied to a case study. The results obtained using the risk measures are compared with a traditional risk-neutral measure: the expected profit. The computational performance of the proposed approach is evaluated. The advantages of using risk-averse measures considering the quality of the solutions are explored. Thus, extreme values for costs, revenues, and profit for the solutions obtained with the different performance measures are shown.

The remainder of this paper is organized as follows. Section 2 presents an analysis of the relevant literature related to the CLSC design and planning problem under uncertainty where risk considerations are taken into account. In Section 3, the underlying problem description is stated. In Section 4, a multistage mathematical framework able to represent the dynamic nature of the network structure is proposed for the multiperiod, multiproduct CLSC design and planning problem with uncertain levels in the amount of raw material and customer demands. Costs associated with production, storage, transportation, and remanufacturing are considered. For the transportation costs, not only operational costs are accounted for but also CO_2 emissions costs are modeled. In Section 5, an example is presented in order to highlight the benefits of the formulation introduced. In Section 6, an analysis of results is performed to illustrate the advantages of using the presented risk-averse formulation. Finally, concluding remarks are given in Section 7.

2. LITERATURE REVIEW

In this section a summary of the most closely related papers to the topic of this work is presented. For further details, the authors suggest reading the review works by Guide and Van Wassenhove,[4] Souza[19] and Govindan et al.[20] As pointed out before, a critical and necessary issue to be considered in CLSC in a volatile market is the design and planning problem, so as to avoid the definition of nonadequate structures that will last for long time periods. In addition, since the effects of the occurrence of given negative uncertain events can be magnified and impact substantially on the CLSCs performance, the handling of risk in these systems is always desirable.

In general, the handling of uncertainty in an optimization context is associated with the development of frameworks that select the best solution according to a given performance measure among those solutions less affected by data variations.

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Thus, the necessity of frameworks to deal with the uncertain market conditions in the design and planning of CLSCs is unavoidable. Some of the most recent and relevant papers associated with the design and planning of CLSCs with uncertain parameters are by Salema et al.;[21] Francas and Minner;[22] Pishvaee et al.;[23] Lee and Dong;[24] Pishvaee et al.;[25] Zeballos et al.;[26] Amin and Zhang;[27] Cardoso et al.;[1] Zeballos et al.;[28] as well as Khatami et al.[29]

The work of Salema et al.[21] was one of the first works addressing the design and planning of CLSC under uncertainty. A generic reverse logistics network was modeled where capacity limits, multiproduct management, and uncertainty on product demands and returns were accounted for. The uncertainty was considered while minimizing the CLSC cost. Francas and Minner[22] used a two-stage stochastic framework with the objective of studying optimal capacity acquisition and expected performance in a CLSC under uncertain demand and returns. The approach was applied to two different fixed network structures and two different market structures when new and remanufactured returned products are flowing through the network. The formulation objective is to maximize the expected profit. Pishvaee et al.[23] developed a scenario-based stochastic approach for an integrated forward/reverse network design with demands, quantity, and quality of returns as well as variable costs as uncertain parameters. The network considered in the paper includes production/recovery, distribution–collection centers, customer, and disposal centers. The model is developed for minimizing the expected costs. Lee and Dong[24] proposed a two-stage stochastic programming model for the design of a multiperiod network. Uncertainty is considered in the demand of forward products and in the supply of returned products at customers. The authors developed a heuristic algorithm based on simulated annealing in order to solve real case studies. In addition, the formulation considers as objective function the minimization of the sum of current investment costs of building facilities and expected future processing and transportation costs. Pishvaee et al.[25] proposed a model based on robust theory (Ben-Tal and Nemirovski[30]) for single-product, single-period forward and reverse chains considering production/recovery, hybrid distribution/collection centers, customers, and disposal centers. The formulation takes into account as uncertain parameters demand, quantity of return flows, as well as transportation costs while minimizing the total costs, which include fixed opening costs and transportation costs. Zeballos et al.[26] introduced a two-stage scenario-based modeling approach in order to deal with the design and planning decisions in multiperiod, multiproduct CLSCs subject to uncertain conditions. In their paper, uncertainty is associated with the quantity and quality of the flow of products of the reverse network. The approach is developed with the underlying objective of the expected profits maximization. Amin and Zhang[27] proposed a mathematical stochastic programming approach based on scenarios for a single-period multiproduct CLSC location problem considering demand and return as uncertain parameters, and including environmental factors on the objective function. The network considered by Amin and Zhang[27] takes into account multiple plants, collection centers and demand markets. The model is proposed to minimize the expected costs. Cardoso et al.[1] developed an optimization framework for generic CLSCs under an uncertain products demand context. The formulation objective is to maximize the expected net present value while the entity capacity expansion and dynamic transportation links are considered. Zeballos et al.[28] proposed a multistage stochastic model for addressing the design and planning of a general CLSC, structured as a 10-layer network with uncertain levels in the amount of raw material supplies and customer demands. The framework performance measure is to minimize the expected cost minus the expected revenue due to the amount of products returned, from repairing and decomposition centers to the forward network. Khatami et al.[29] introduced a two-stage mathematical formulation for designing a multiperiod multicommodity CLSC network under uncertainty. The model determines the initial capacity of new facilities and the amount of capacity expansion for existing ones. The formulation objective function is to minimize the investment costs and the expected value of the operational costs. In addition, to solve a real-life case, the authors applied a Benders' decomposition method.

The above papers consider as objective function expected values of some relevant magnitudes (e.g., cost, revenue, and profit), and the effect of risk is not taken into account. Therefore, the approaches are risk neutral. Few papers have been proposed including risk-averse formulations in SC management. Some of the most recent and relevant works in SC are by Soleimani et al.,[12] Gebreslassie et al.,[31] Cardoso et al.,[32] and Subulan et al.[33] Soleimani et al.[12] developed a two-stage stochastic framework to deal with the single-period location–allocation problem in a CLSC with demand and prices of new and return products as uncertain parameters. The authors used three types of risk measures as risk criteria: MAD, VaR, and CVaR, when the total profits are considered as an objective function. It is important to note that risk measures are applied only to costs, and revenues are considered in the performance measure as expected values. Gebreslassie et al.,[31] proposed a bicriterion, multiperiod, two-stage stochastic approach to address the optimal design of hydrocarbon biorefinery supply chains under supply and demand uncertainties. The model objective is the simultaneous minimization of the expected annualized cost and the financial risk. The authors applied CVaR and downside risk in order to minimize the risk associated with scenarios whose costs exceed certain limits. The formulation determines the optimal network design, technology selection, capital investment, production planning, and logistics management decisions. Cardoso et al.[32] introduced a model for the design and planning of CLSCs under only demand uncertainty that maximizes the expected net present value (ENPV) and minimizes risk associated with net present value (NPV). The authors implemented four risk measures (variance, variability index, downside risk, and CVaR) in order to compare their performances. In this work the risk measures address the NPV as a global function where the trade-off between the particular risks connected with the increment of costs and decrease of revenues is not explicitly represented. Subulan et al.[33] introduced a multistage scenario based stochastic and possibilistic approach for the optimal design for the CLSC network of the lead/acid battery industry with financial and collection risks. The authors included in the approach different risk measures, such as variability index, downside risk, and CVaR, in order to take into account the total cost and the total collection coverage as general objective functions.

From the analyzed works it can be concluded that few works have addressed the design and planning of generic CLSCs under uncertainty while simultaneously considering a risk-averse objective related to profit. In addition, most of the

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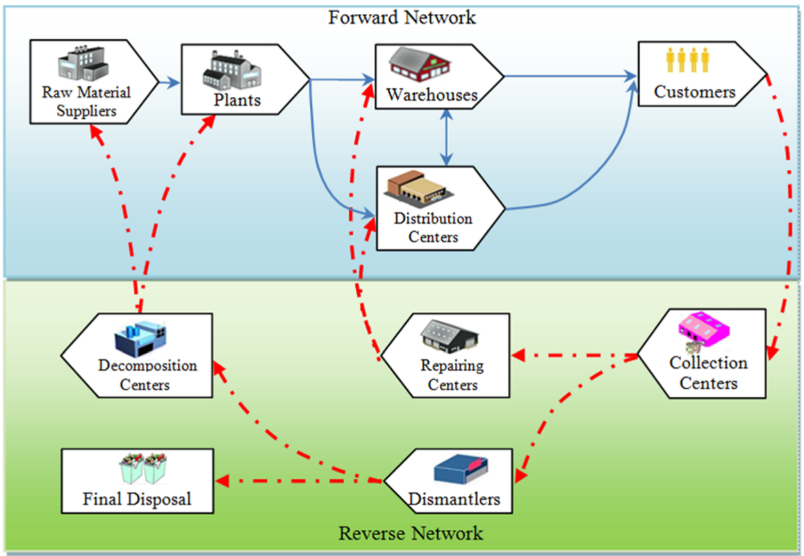

Figure 1. Network structure.

mentioned works addressed only the risk associated with costs without considering the network revenues. Thus, a key aspect of the proposed work is the consideration of a multiobjective function where the maximization of the expected profit is combined with the fundamental idea of risk management incorporated through the explicit trade-off between risk associated with costs and revenues. On the other hand, opening/closing entities during the planning horizon has almost not been considered in a multistage stochastic approach. Thus, based on the mentioned related papers and to the best of our knowledge, a joint consideration of problem aspects, such as (1) a generic multiperiod multiproduct CLSC with a general network structure of ten types of entities, (2) risk-averse objectives associated with both costs and revenues, (3) a flexible network structure, (4) transport capacity, (5) salvage grade of returned products, (6) CO_2 emissions of the transport system, as well as (7) minimum and maximum storage and processing capacity limits for network entities, has not been addressed in a comprehensive manner in a multistage stochastic approach. Moreover, this paper presents a comprehensive comparison of several risk metrics for the design and planning problem under uncertainty in supply and customer demands.

3. PROBLEM STATEMENT

The problem addressed in this article deals with the design and planning problem of CLSCs under uncertain conditions. The proposed network structure is general, including 10 types of entities: raw material suppliers, factories, warehouses, distribution centers, customers, collection centers, dismantlers, repairing centers, final disposal locations, and decomposition centers. Facilities can be opened/closed at the beginning of any time period during the time horizon. Figure 1 illustrates the studied network structure and the possible product flows among the entities. The product types and quantities to be manufactured, transported, stored, and recycled are determined for each period, taking into account the decisions adopted in the previous periods. The problem objective is to determine the design and the planning of the network for each period while network profits are maximized. A part of the problem is intended to find the initial network design that copes with the uncertain parameters, and guarantees the network performance stability where changes to particular realizations of the scenarios are allowed.

The problem features considered in this paper can be stated as follows. The planning horizon is divided into several time periods. Locations and capacities of possible network entities are known in advance. The opening/closing of the network entities is decided at the beginning of each period. Types and capacities of possible transport system units, as well as the distances between entities, are known and fixed. Products flowing through the network are grouped according to their salvage grade (e.g., nonreusable, partially reusable, fully reusable). Customers are not able to distinguish between new and recycled products. The unit costs of storage, transportation, purchasing, and CO_2 emissions are known and fixed. The number of recycled products depends on the satisfied demand level. Not all products are recovered after being purchased by customers. Rates at which products discarded by end users flow through the reverse network depend on their origin and destination entities. The uncertainties arise from the customer demand and raw material supply. Minimum and maximum storage capacity limits for network entities are enforced. Plants have maximum and minimum processing levels.

4. PROBLEM FORMULATION

A stochastic approach is employed to deal with different uncertain levels of customer demand and raw material supply, as well as to incorporate it in a multiperiod design-planning model. Thus, among all feasible solutions to the design and planning problem explicitly considering the measurement of the risk associated with costs and revenues, the formulation is oriented to find the solution that should remain almost invariant in performance when the parameters adopt any of the uncertain values. In order to address the risk, several popular functions based on variance and CVaR are considered. Five functions are considered with the objective of evaluating the advantages/disadvantages of such measures when solving the design and planning problem of CLSCs with a multistage stochastic approach.

Owing to the fact that, in this paper, the design of the network can change during the time horizon, design decisions must be determined at the beginning of the first time period

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(t_0), and reviewed at the start of subsequent periods (t_1 to $t_{f\text{-}1}$), so as to contribute to the maximization of the objective function. Tactical decisions, such as those related to production, transportation, distribution, and storage, are determined at the beginning of the periods t_1 to t_f. Following a multistage stochastic formulation structure, the approach adopts the network design decisions of the first period (t_0) as the "first-stage variables". That is, these variables are the ones that must be determined before the resolution of the underlying uncertainty and, therefore, the values taken by these variables must be consistent with all possible uncertain conditions. Oppositely, the design variables corresponding to periods t_1 to $t_{f\text{-}1}$ as well as the decisions related to operational activities (production, transportation, distribution, and storage) are variables subject to adjustment when specific realizations of uncertain parameters occur. The last mentioned set of variables is associated with different stages, and it is used to fix any infeasibility taking place due to a given revelation of the uncertain parameters. It is worth noting that, given the multistage nature of the formulation, there is a subset of variables in each time period. Thus, the approach is able to represent the dynamic nature of the closed-loop supply chain due to each subset of variables that allow adopting corrective decisions considering the uncertainty previously realized and the network configuration determined by the first stage variables.

In the proposed formulation the uncertainty of the supply and demand is represented by a finite number of scenarios due to the assumption that the real probability distribution can be approximated by discrete probability distributions. Given the mentioned assumption and the Bmulti-stage nature of the formulation, a multilayered scenario tree is used to address the uncertainty since demand and supply are considered as dynamic parameters varying through the time periods. Each tree node represents the individual effects of two uncertain parameters (demand and supply), since they are considered as independent stochastic processes. Therefore, a given level of demand and supply at a given time period is represented by a node. A scenario is formed by the nodes located on the ensuing branch tree, starting with the root node and ending with a particular leaf node at the last time period. Each node in the scenario tree represents a possible company operating state, linked to specific levels of demand and supply.

4.1. Model. The general goal of the stochastic model is to maximize the company profit, taking into account costs due to raw material consumption, storage, transportation, CO2 emissions, as well as facility costs. The approach aims at generating the CLSC design for the first period, while at the same time evaluating possible changes in the network structure as well as the planning activities (production, transportation, distribution, and storage) at the next time periods. The network structure variations and the planning decisions protect the corporation against all the possible outcomes characterized in the considered scenarios. In addition, the use of the framework avoids minor alterations of the uncertain parameters that cause significant changes in the network performance.

It is worth noting that the risk management can be incorporated into the formulation by means of suitable utility functions and/or into constraints. In this work, the risk is mainly taken into account through the objective functions, which have some associated constraints. Considering the importance of the performance measure in stochastic approaches, in this paper six performance measures are considered: the expected profits and five types of measures that include risk aversion. The expected profits do not consider the effects of the variability of random outcomes, and it is included for comparative purposes. Alternatively, the other five measures are appropriate for quantifying the risk. In addition, they can be included in mathematical approaches without changing the linear condition of the formulation. It is important to note that the incorporation of risk criteria in optimization formulations allows coping with real volatile markets, by trying to achieve solutions less affected by changes in the uncertain parameters.

Having in consideration the problem description, the mathematical formulation of the multistage stochastic linear programming approach is presented next. The description starts with the objective functions. Model nomenclature is included in Appendix A.

4.1.1. Objective Functions. Different elemental terms compose the objective functions presented below. Starting with the term in eq 1, RVN, this represents the revenues achieved by selling products to customers. It is computed for each scenario s considering time periods t_1 to t_f, all transportation modes and all products sent to customers (I_c) from warehouses (I_w) and distribution centers (I_{dc}). It is important to note that each scenario $s \in SC$ is defined by a given sequence of events Ω_{nt} from the root node until a particular leaf node at the last time period. Ω_{nt} denotes the events $es \in Es$ and $ed \in Ed$ that occur for node n at time period t.

$$\mathrm{RVN}_s\colon \sum_{t\epsilon T/t_0} \sum_{i\epsilon(I_w \cup I_{dc}), i'\epsilon I_c} \sum_{p\epsilon PR} \sum_{r\epsilon TR} \sum_{n\epsilon\{NS_s \cap NT_t\}} pp_{pt} x_{ii'prtn} \tag{1}$$

Term 2, PRT, denotes the revenues obtained by introducing recovered products/materials into the forward network. It is computed for each scenario s considering time periods t_1 to t_f, all transportation modes and all products that are returned from the reverse network to the forward network (A^{rf}).

$$\mathrm{PRT}_s\colon \sum_{t\epsilon T/t_0} \sum_{i,i'\epsilon A^{rf}} \sum_{p\epsilon PR} \sum_{r\epsilon TR} \sum_{n\epsilon\{NS_s \cap NT_t\}} pc_{pt} x_{ii'prtn} \tag{2}$$

Term 3, COF, symbolizes the costs for opening facilities at the beginning of the planning horizon (t_0). Time t_0 corresponds to the root node of the tree scenarios, and is common for all scenarios s.

$$\mathrm{COF}\colon \sum_{i\epsilon I} \sum_{t\epsilon T/t_0} \sum_{n\epsilon N/n_0} fcc_i y_{itn} \tag{3}$$

Term 4, COCF, represents the costs for opening and closing facilities for periods t_1 to $t_{f\text{-}1}$, which is dependent on the scenarios. It is computed for each scenario s considering all entities available in the network.

$$\mathrm{COCF}_s\colon \sum_{i\epsilon I} \sum_{t\epsilon T\backslash\{t_0 \cup t_f\}} \sum_{n\epsilon\{NS_s \cap NT_t\}} fco_i yc_{itn} + \sum_{i\epsilon I} \sum_{t\epsilon T\backslash\{t_0 \cup t_f\}} \sum_{n\epsilon\{NS_s \cap NT_t\}} fcc_i yo_{itn} \tag{4}$$

Term 5, TEC, denotes the transportation and CO_2 emissions costs of the forward and reverse networks, for each transportation mode and product, considering time periods t_1 to t_f. It is computed for each scenario s considering all products transported between two entities (A).

$$\text{TEC}_s\text{:}\ \sum_{t\epsilon T\setminus t_0}\ \sum_{i,i'\epsilon A}\ \sum_{p\epsilon PR}\ \sum_{r\epsilon TR}\ \sum_{n\epsilon\{NS_s\cap NT_t\}} dst_{ii'}(c_{ii'rt} + ee_{ii'rt})x_{ii'prtn} \tag{5}$$

Term 6, PUC, represents the purchasing costs of raw material transported from suppliers to plants. It is computed for each scenario s considering all products, transportation modes, and time periods t_1 to t_f.

$$\text{PUC}_s\text{:}\ \sum_{t\epsilon T\setminus t_0}\ \sum_{i,i'\epsilon A^{sf}}\ \sum_{p\epsilon PR}\ \sum_{r\epsilon TR}\ \sum_{n\epsilon\{NS_s\cap NT_t\}} u_{ipt}x_{ii'prtn} \tag{6}$$

Term 7, STC, denotes the storage costs over time periods t_1 to t_f and all entities as well as products.

$$\text{STC}_s\text{:}\ \sum_{t\epsilon T\setminus t_0}\ \sum_{i\epsilon I}\ \sum_{p\epsilon PR}\ \sum_{n\epsilon\{NS_s\cap NT_t\}} stc_{ipt}z_{iptn} \tag{7}$$

4.1.1.1. Expected Profits. The performance measure (eq 8) is included in the work for comparative purposes due to it being the main objective function employed in risk-neutral formulations.

$$\begin{aligned} &\textit{Maximize Expected Profits}\\ &\quad = \textit{Expected Revenues} - \textit{Expected Operational Costs}\\ &\qquad - \textit{Supply Chain Structure Costs} \end{aligned} \tag{8}$$

The expected profit is computed using terms 9 and 10. Term 9, ER, represents the expected revenues by selling new and recycled products. On the other hand, term 10, EOC, denotes the expected operational costs related to raw material consumption, storage, transport, and emissions. Thus, terms RVN_s, PRT_s, COCF_s, TEC_s, PUC_s, and STC_s (eqs 1, 2, 4, 5, 6, and 7), which depend on the scenario $s\in SC$ and the occurrence probability (Pb_s), are employed to compute ER and EOC. The supply chain structure costs (COF) were defined above in eq 3. Finally, the expected profits (EP) (eq 11) include three elements: the expected revenues (ER), the expected operational costs (EOC), and the supply chain structure costs (COF). It is worth noting that only the first two terms depend on the scenarios. Thus, the objective function of the model (OFEP), which is shown in term 12, is the maximization of the expected profits (ER-EOC), minus the costs for opening facilities at the beginning of the planning horizon (COF).

$$\text{ER:}\ \sum_{s\epsilon SC} Pb_s(RVN_s + PRT_s) \tag{9}$$

$$\text{EOC:}\ \sum_{s\epsilon SC} Pb_s(COCF_s + TEC_s + PUC_s + STC_s) \tag{10}$$

$$\text{EP: } ER - EOC - COF \tag{11}$$

$$\text{OFEP: } \max EP \tag{12}$$

4.1.1.2. General Form of the Objective Function with a Risk Measure. In this section, five performance measures are considered. The general form of the objective functions taking into account the risk aversion is

$$\begin{aligned} &\textit{Maximize Profit Variability}\\ &\quad = \textit{Expected Revenues} - \textit{Expected Operational Costs}\\ &\qquad - \textit{Supply Chain Structure Costs} - \lambda\ (\textit{Risk Measure}) \end{aligned} \tag{13}$$

The objective function regards the expected revenues and costs as well as a risk measure. It is worth noting that the general form of the proposed performance measure can be considered as a mean-risk framework. The last term is affected by a non-negative weighted factor (λ), which is a trade-off coefficient representing the relationship between the risk and the expected values.

4.1.1.3. Linear Measure of the Profits Variability (LMPV). LMPV is an absolute deviation, as proposed by Yu and Li,[34] which is converted to a linear formulation by introducing non-negative deviational variables (Wagner[35]). This measure is used in this work with the objective of avoiding the quadratic term that includes the traditional Markowitz mean-variance model. The LMPV uses two deviational variables (dvr_s and dvc_s) subject to original problem constraints and additional soft constraints. While dvr_s is used for quantifying the revenues variability, dvc_s is employed for computing the costs variability. Thus, terms 14 and 15 denote the practical implementation of the linear measure of the revenues variability (LMRV) and the linear measure of the costs variability (LMCV), respectively. On the other hand, constraints 16 and 17 are the additional soft constraints in order to ensure positive values of the difference inside the absolute function for revenues and costs. The deviational variable dvr_s is equal to zero ($dvr_s = 0$) when ($\boldsymbol{RVN_s} + \boldsymbol{PRT_s}$) is greater than ER. On the other hand, if ER is greater than ($\boldsymbol{RVN_s} + \boldsymbol{PRT_s}$), then $dvr_s = ER - (\boldsymbol{RVNs} + \boldsymbol{PRT_s})$. The deviational variable dvc_s is equal to zero ($dvc_s = 0$) when EOC is greater than ($\boldsymbol{COCF_s} + \boldsymbol{TEC_s} + \boldsymbol{PUC_s} + \boldsymbol{STC_s}$). In contrast, if ($\boldsymbol{COCF_s} + \boldsymbol{TEC_s} + \boldsymbol{PUC_s} + \boldsymbol{STC_s}$) is greater than EOC, then $dvc_s = (\boldsymbol{COCF_s} + \boldsymbol{TEC_s} + \boldsymbol{PUC_s} + \boldsymbol{STC_s}) - EOC$. Finally, the objective function OFLMPV (eq 18) is to maximize a combination of three terms, EP, LMRV, and LMCV, subject to original problem constraints and terms 16 and 17

$$\text{LMRV:}\ \sum_{s\epsilon SC} [Pb_s((RVN_s + PRT_s) - ER) + 2dvr_s] \tag{14}$$

$$\begin{aligned} \text{LMCV:}\ \sum_{s\epsilon SC} &[Pb_s(EOC - (COCF_s + TEC_s\\ &+ PUC_s + STC_s)) + 2dvc_s] \end{aligned} \tag{15}$$

$$ER - (RVN_s + PRT_s) \leq dvr_s \qquad \forall\ s \in SC \tag{16}$$

$$\begin{aligned} &(COCF_s + TEC_s + PUC_s + STC_s) - EOC \leq dvc_s\\ &\quad \forall\ s \in SC \end{aligned} \tag{17}$$

$$\text{OFLMPV: } \max EP - \lambda(LMRV + LMCV) \tag{18}$$

4.1.1.4. Modified Linear Measure of the Profits Variability (MLMPV). In this case, the objective function OFMLMPV (eq 41) is a variation of OFLMPV, where constraints (eqs 16 and 17) as well as the deviational variables dvr_s and dvc_s are used to compute only the revenues decrement as well as the costs increment, respectively. While the term in eq 19 denotes the practical implementation of MLMPV, constraints (eqs 16 and 17) are the additional soft constraints in order to determine the difference between the expected values and the magnitudes of each scenario for revenues and costs. Therefore, the use of OFMLMPV includes also constraints (eqs 16, 17, and 19). From a practical point of view, this objective function penalizes the set of scenarios associated with the occurrences of uncertain parameters that decrease the revenues and increase the costs of the company.

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Ind. Eng. Chem. Res. 2016, 55, 6236−6249

$$\text{MLMPV: } \sum_{s \in SC} [Pb_s(dvr_s + dvc_s)] \quad (19)$$

$$\text{OFMLMPV: } \max EP - \lambda MLMPV \quad (20)$$

4.1.1.5. Conditional Value at Risk. The following three objective functions use the concept behind the mathematically well-behaved risk measure conditional value at risk. CVaR is a popular tool for managing risk, which has been shown to be superior to VaR in optimization applications (Rockafellar and Uryasev[17,18]). Since in the proposed work it is assumed that the uncertain parameters are represented by a finite number of scenarios, the three performance measures use the CVaR function obtained by Noyan[7] for the case of finite probability space.

The first risk measure used in this paper is CVaRc (eq 21), which is employed to reduce the likelihood that the design and planning of a given CLSC incur large costs for certain scenarios. When considering large confidence levels (small values of parameter αc), more scenarios are taken into account during the search process, and therefore, the solution becomes more averse to incurring large costs. Thus, formally, the confidence level is associated with the complement of parameter αc $(1 - \alpha c)$. The practical implementation of the risk measure that exceeds a given value at risk imposed by a confidence level requires the soft constraint (eq 22) in order to determine the difference between a given level of costs (ηc) and the costs of the scenarios that are outside of the confidence interval. ηc is determined during the optimization process as a function of the selected confidence level. The deviational variable $dv\eta c_s$ is greater than zero when $(\boldsymbol{COCF_s} + \boldsymbol{TEC_s} + \boldsymbol{PUC_s} + \boldsymbol{STC_s})$ is greater than ηc. Thus, the variable $dv\eta c_s$ quantifies the increment of the costs of certain scenarios when their values are greater than ηc.

The performance measure to be maximized is OFCVaRc (eq 23), which requires the inclusion of constraints 21 and 22. The final form of the objective function is obtained after considering simultaneously the expected profits and risk measurement considering only the costs variability. In this case, OFCVaRc includes three terms: the expected profits (ER-EOC), the cost for opening facilities at the beginning of the planning horizon (COF), and the term CVaRc. It is important to note that COF does not depend on the stages and it is affected by the factor $(1 + \lambda)$ due to the application of the CVaR concept to the costs variability. The steps for achieving the utility function (eq 23) from a performance measure of the type *Mean-CVaR* was proved by Noyan.[7]

$$\text{CVaRC: } \eta c + \frac{1}{(1 - \alpha c)} \sum_{s \in SC} [Pb_s(dv\eta c_s)] \qquad \forall\ s \in SC\eta c \quad (21)$$

$$(COCF_s + TEC_s + PUC_s + STC_s) - \eta c - dv\eta c_s \le 0 \qquad \forall\ s \in SC \quad (22)$$

$$\text{OFCVaRc: } ER - EOC - (1 + \lambda)COF - \lambda CVaRc \quad (23)$$

The second risk function (eq 24) is used to bound the probability that the design and planning of a given CLSC incur large decreases in revenues for certain scenarios. The solutions become more averse to incur in small revenues when considering large confidence levels. In this case, the complement of the parameter αr is associated with the confidence level. It is important to note that terms 24 and 25 arise from the application of the general definition of CVaR to the revenues variability for the case of finite probability space. While term 24 denotes the practical implementation of a risk measure of the revenues that decrease below a given value at risk imposed by the confidence level, constraint 25 determines the difference between a given level of revenues (ηr) and the sales of the scenarios that are outside of the confidence interval. ηr is determined during the optimization process as a function of the selected confidence level. The deviational variable $dv\eta r_s$ is greater than zero when $(\boldsymbol{RVN_s} + \boldsymbol{PRT_s})$ is less than ηr. The variable $dv\eta r_s$ quantifies the reduction of sales of the scenario s when its revenues are less than ηr.

It is worth noting that the objective function OFCVaRr (eq 26) requires the inclusion of constraints 24 and 25. In this case, the performance measure structure is obtained taking into account simultaneously the expected profits and risk measurement considering the revenues variability. OFCVaRr includes three terms: the expected profits (ER-EOC), the costs for opening facilities at the beginning of the planning horizon (COF), and the term CVaRr. Contrary to the case of OFCVaRc, the application of the CVaR concept to the revenues variability lead to a final performance measure where the term COF is not affected by the factor $(1 + \lambda)$.

$$\text{CVaRr: } \eta r - \frac{1}{(1 - \alpha r)} \sum_{s \in SC} [Pb_s(dv\eta r_s)] \qquad \forall\ s \in SC\eta c \quad (24)$$

$$(RVN_s + PRT_s) - \eta r + dv\eta r_s \ge 0 \qquad \forall\ s \in SC \quad (25)$$

$$\text{OFCVaRr: } ER - EOC - COF + \lambda CVaRr \quad (26)$$

Finally, a function that includes simultaneously measures of the risk effects when considering costs and revenues is presented. It is worth remarking that the practical implementation of the performance measure OFCVaR (eq 27) requires the inclusion of constraints 21, 22, 24, and 25. The final form of the performance measure is obtained after considering simultaneously the expected profits and risk measurement of costs and revenues. Thus, the objective function (eq 27) is a performance measure of the type *Mean-CVaR* that includes four terms: the expected profit (ER-EOC), the costs for opening facilities at the beginning of the planning horizon (COF) (affected by the factor $(1 + \lambda)$ due to application of the CVaR concept to the costs variability), and the terms CVaRc and CVaRr.

$$\text{OFCVaRrc: } ER - EOC - (1 + \lambda)COF + \lambda CVaRr - \lambda CVaRc \quad (27)$$

4.1.2. Model Constraints. The model constraints are of different types and describe the problem characteristics, as will be detailed below:

$$\sum_{(i,i')\epsilon A} \sum_{p\epsilon PR} \sum_{r\epsilon TR} x_{ii'prtnc} \le M \sum_{nf\epsilon Na_{nc}} y_{it-1nf} \qquad \forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (28)$$

$$\sum_{(i,i')\epsilon A} \sum_{p\epsilon PR} \sum_{r\epsilon TR} x_{ii'prtnc} \le M \sum_{nf\epsilon Na_{nc}} y_{it-1nf} \qquad \forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (29)$$

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Ind. Eng. Chem. Res. 2016, 55, 6236−6249

$$y_{it-1nf} - y_{itnc} \leq yc_{itnc}$$
$$\forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t,\ \forall\ nf\epsilon Na_{nc} \quad (30)$$

$$y_{itnc} - y_{it-1nf} \leq yo_{itnc}$$
$$\forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t,\ \forall\ nf\epsilon Na_{nc} \quad (31)$$

$$e_{ii'rtnc} \leq M \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ (i,\ i')\epsilon A,\ \forall\ r\epsilon TR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (32)$$

$$e_{ii'rtnc} \leq M \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ (i,\ i')\epsilon A,\ \forall\ r\epsilon TR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (33)$$

$$\sum_{i'\epsilon(I_w\cup I_{dc})} \sum_{r\epsilon TR} x_{i'iprtn} \geq d_{ipted}$$
$$\forall\ i\epsilon I_c,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\},\ \forall\ (ed,\ es)\epsilon\Omega_{nt} \quad (34)$$

$$\sum_{i':(i,i')\epsilon A^{sf}} \sum_{r\epsilon TR} x_{ii'iprtn} \geq Rmn_{iptes} y_{itn}$$
$$\forall\ i\epsilon I_s,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\},\ \forall\ (ed,\ es)\epsilon\Omega_{nt} \quad (35)$$

$$\sum_{i':(i,i')\epsilon A^{sf}} \sum_{r\epsilon TR} x_{ii'iprtn} \leq Rmx_{iptes} y_{itn}$$
$$\forall\ i\epsilon I_s,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\},\ \forall\ (ed,\ es)\epsilon\Omega_{nt} \quad (36)$$

$$\sum_{i':(i',i)\epsilon A^f} \sum_{r\epsilon TR} x_{i'iprtn} - z_{iptn} = \sum_{j:(i,j)\epsilon A^f} \sum_{r\epsilon TR} x_{ijprtn}$$
$$\forall\ i\epsilon I^f,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T/\{t_1\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\} \quad (37)$$

$$\sum_{i':(i',i)\epsilon A^{rf}} \sum_{r\epsilon TR} x_{i'ipr(t-1)n} + z_{ip(t-1)n} + \sum_{i':(i',i)\epsilon A^f} \sum_{r\epsilon TR} x_{i'iprtn} - z_{iptn} = \sum_{j:(i,j)\epsilon A^f} \sum_{r\epsilon TR} x_{ijprtn}$$
$$\forall\ i\epsilon I^f,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0,t_1\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\} \quad (38)$$

$$\sum_{i':(i',i)\epsilon A^r} \sum_{r\epsilon TR} rl_{ipt} x_{i'iprtn} - z_{iptn} = \sum_{j:(i,j)\epsilon A^r} \sum_{r\epsilon TR} x_{ijprtn}$$
$$\forall\ i\epsilon I^r,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T/\{t_1\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\} \quad (39)$$

$$z_{ip(t-1)n} + \sum_{i':(i',i)\epsilon A^r} \sum_{r\epsilon TR} rl_{ipt} x_{i'iprtn} - z_{iptn} = \sum_{j:(i,j)\epsilon A^r} \sum_{r\epsilon TR} x_{ijprtn}$$
$$\forall\ i\epsilon I^r,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0,t_1\},\ \forall\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\} \quad (40)$$

$$ff_{ipt} \sum_{i':(i,i')\epsilon A^r} \sum_{r\epsilon TR} x_{ii'prtn} = \sum_{j:(i,j)\epsilon A^{rc}} \sum_{r\epsilon TR} x_{ijprtn}$$
$$\forall\ i\epsilon I^r\backslash\{I_{fd} \vee I_c\},\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ s\epsilon SC,\ \forall\ n\epsilon\{NT_t \cap NS_s\} \quad (41)$$

$$\sum_{p\epsilon PR} x_{ii'prtn} \geq trmn_{ii'r} e_{ii'rtn}$$
$$\forall\ (i,\ i')\epsilon A,\ \forall\ r\epsilon TR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ n\epsilon NT_t \quad (42)$$

$$\sum_{p\epsilon PR} x_{ii'prtn} \leq trmx_{ii'r} e_{ii'rtn}$$
$$\forall\ (i,\ i')\epsilon A,\ \forall\ r\epsilon TR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ n\epsilon NT_t \quad (43)$$

$$\sum_{p\epsilon PR} z_{iptnc} \geq Imn_i \sum_{nf\epsilon Na_{nc}} y_{it-1nf} - Imn_i(1 - y_{itnc})$$
$$\forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0,\ t_f\},\ \forall\ nc\epsilon NT_t \quad (44)$$

$$\sum_{p\epsilon PR} z_{iptnc} \geq Imn_i \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ i\epsilon I,\ \forall\ t\epsilon T/\{t_f\},\ \forall\ nc\epsilon NT_t \quad (45)$$

$$\sum_{p\epsilon PR} z_{iptnc} \leq Imx_i \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ i\epsilon I,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (46)$$

$$\sum_{i':(i,i')\epsilon A} \sum_{r\epsilon TR} x_{ii'prtnc} \geq Pmn_{ipnc} \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ i\epsilon I,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (47)$$

$$\sum_{i':(i,i')\epsilon A} \sum_{r\epsilon TR} x_{ii'prtnc} \leq Pmx_{ipnc} \sum_{nf\epsilon Na_{nc}} y_{it-1nf}$$
$$\forall\ i\epsilon I,\ \forall\ p\epsilon PR,\ \forall\ t\epsilon T\backslash\{t_0\},\ \forall\ nc\epsilon NT_t \quad (48)$$

Constraints 28 and 29 allow a given entity to receive and send products whether or not it was open at time period $t - 1$. Constraint 30 determines the time at which a given network entity goes from open to closed. On the other hand, constraint 31 specifies the time at which a given entity goes from closed to open. Constraints 32 and 33 allow the existence of incoming and outgoing transportation moves at time t if a given entity belongs to the network at time period $t - 1$. Constraint 34 determines the minimum value of customer demand for a given event $ed \in Ed$, which depends on time period t and scenario node n $((ed, es)\epsilon\Omega_{nt})$. Constraints 35 and 36 set the maximum and minimum bounds for the supply capacity of raw material when the event $es \in Es$ occurs at time period t of node n $((ed, es)\ \epsilon\ \Omega_{nt})$. Equations 37 to 40 represent the material balance in the closed-loop supply chain. Thus, while eqs 37 and 38 are related to the forward network, eqs 39 and 40 are associated

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Ind. Eng. Chem. Res. 2016, 55, 6236−6249

Table 1. Results for Different Performance Measures

Case	αc	αr	λ	Objective Function [c.u.][a]	Expected Profit [c.u.]	CPU Time [s]
OFEP				759540380	759540380	1314
OFLMPV			1	742569630	746104649	683898
OFMLMPV			1	745607978	749585839	19995
OFCVaRc	0.1		1	220177690	726721888	18574
OFCVaRr		0.1	1	2068362269	756843536	12707
OFCVaRcr	0.1	0.1	1	1513818875	759440183	19142

[a][c.u.] currency units.

with the reverse network. Constraints 37 and 39 are the material balance at time period t_1. Constraints 38 and 40 are the material balance at any time period greater than t_1. It is important to note that eq 11 considers the flow of products sent by the reverse network entities to the forward network facilities. The parameter rl_{ipt} is used in constraints 39 and 40, and it represents the percentage of product p sent from entity i to the subsequent entities in the reverse network at time t. This parameter receives the value of η when the network arc connecting customers to collection centers is considered. Constraint 41 represents the way in which the products flow through the reverse network. The parameter ff_{ipt} takes different values (ϵ, ε, δ, χ) depending on the entity i taken into account. For example, the ff_{ipt} parameter takes the value of ϵ when considering the product flow from collection centers to repairing centers. The rest of products $(1 - ff_{ipt})$ are sent to dismantlers by default. Constraints 42 and 43 limit the maximum and minimum transportation capacity between two entities i and $\acute{i}$, at a particular time period and using a specific transportation mode r. Constraints 44 and 45 bound the minimum amount of products stored in the network entities. Constraint 44 imposes the lower limit at time periods t_1 to t_{f-1} when a given entity belonging to the network at time t-1 remains open during the next period t. Constraint 45 is formulated for enforcing the lower storage limit at the last time period t_f. Constraint 46 bound the maximum amount of products stored in the network entities. Constraint 46 imposes the upper limit at time periods t_1 to t_f. Constraints 47 and 48 apply the minimum and maximum processing capacity at time t of entity i, belonging to the forward network at time $t - 1$.

5. CASE STUDY

The developed risk-averse stochastic approach is applied to a CLSC with a superstructure composed of 3 suppliers (s), 3 factories (f), 2 warehouses (w), 2 distribution centers (dc), 8 customers (c), 3 collection centers (cc), 2 dismantlers (d), 2 repairing centers (rc), 2 final disposals (fd), and 2 decomposition centers (dp). The case study is based on the example introduced by Paksoy et al.[36] for the single-period planning problem of a CLSC. The reference problem has been modified in order to highlight the benefit of the formulation and the risk measures considered in this work. The problem involves a planning horizon of two periods (each equal to five years). Products flowing through the network are grouped into three types: products with a recycle rate of 0% (Nonreusable, Nrcy), 50% (Partially recyclable, Prcy), and 100% (Fully recyclable, Frcy). In the reverse network, the movement of products is described by different rates of flows that depend on the type of product. Thus, the product flow through the reverse network entities is described by $\epsilon = 0.4$, $\chi = 0.7$, $\varepsilon = 0.7$, and $\delta = \{(\delta_{Frcy}, \delta_{Prcy}, \delta_{Nrcy}) = (1,0.7,0)\}$. Three possible levels for the uncertain condition of raw material supply and customer demand are considered. (es_1, es_2, es_3) and (ed_1, ed_2, ed_3) are the outcomes for describing the uncertainty of the parameters. Two types of trucks form the transportation system. Specific unit CO_2 emissions and transportation costs are associated with each truck type. The problem addressed involves deciding the design and planning of the network for each period considered in the planning horizon, while at the same time the profit maximization is pursued. Data used in the example problem are included in Tables B.1 to B.13 in Appendix B.

6. RESULTS AND SOLUTION ANALYSIS

The proposed multistage framework with risk-averse considerations was coded in GAMS (release 23.6.3) optimizer software, and all computations were run with CPLEX 12.2, on a HP Z800 workstation with Intel Xeon x5650 2.66 GHz and 32 GB RAM memory for a 0.01 gap tolerance.

As the case study involves three possible levels for the uncertain conditions of raw material supply and customer demand, as well as a planning horizon with two time periods, the multistage context considered in the formulation lead to a multilayered tree with 91 nodes for 81 scenarios (1 root node, 9 nodes in the first layer, and 81 nodes in the second layer). Consequently, the computational effort for solving the stochastic approach based on a multilayered tree with 81 scenarios is huge. Thus, with the aim of addressing the problem, from a practical point of view, a scenario reduction algorithm is used. It is important to note that the idea behind the use of the scenario reduction algorithm is to get a reasonably good approximation of the original problem (Dupacova et al.;[37] Heitsch and Romisch;[38] Growe-Kuska et al.[39]). Several algorithms for reducing scenarios are available in the library SCENRED of GAMS (GAMS/SCENRED Documentation[40]). A mix of fast backward and forward algorithms is used with the objective of obtaining a reduced mathematical formulation for the example. In this case, the reduced tree maintains 70% of the original information contained in the tree. It is important to note that, from a practical point of view and for the case study considered, this level of information represents a good balance between a reasonable representation of the original tree and the computational effort to solve it. The multilayered tree obtained after applying the reduction algorithm is composed of 13 scenarios with 17 nodes (1 root node, 3 nodes in the first layer, and 13 nodes in the second layer).

6.1. Risk-Averse Measures.

The advantages of the proposed stochastic programming approach using different utility functions are analyzed. The solutions obtained with the stochastic approach considering the existence of risk are compared with the features of the solution obtained considering expected values.

Table 1 presents the results obtained when solving the formulation with six objective functions: the expected profits

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Ind. Eng. Chem. Res. 2016, 55, 6236−6249

(risk neutral, OFEP) and five measures that include risk criteria: OFLMPV, OFMLMPV, OFCVaRc, OFCVaRr, and OFCVaRcr. In all cases, the scenario tree with 13 scenarios was used. The CVaR parameters, αc and αr, adopt the value 0.1, as this value represents a high level of risk aversion.[10]

As the objective functions values are not a proper criterion to compare the results due to the terms of the performance measures, Table 1 also includes the expected profits obtained with each objective function. Considering the computational performance, OFEP presents the biggest expected profit and the lowest CPU time. Nevertheless, the solution obtained with OFEP does not take into account the risk associated with the occurrence of given uncertain events. These are accounted for when using the risk measures, and from the results it can be easily observed that OFCVaRcr achieves the best expected profits. It is important to note that OFCVaRcr involves the simultaneous application of the CVaR concept, which has proved its advantages in several subjects (Noyan;[7] McNeil et al.[15]), to costs and revenues.

Figures 2, 3, and 4 show the lowest, expected, and highest costs, revenues, and profits obtained for each of the six utility

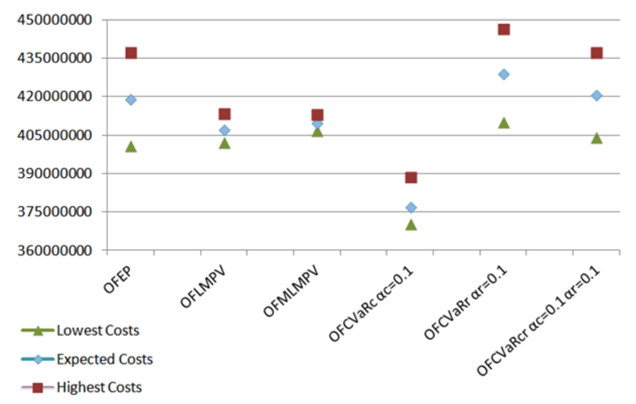

Figure 2. Lowest, expected, and highest costs.

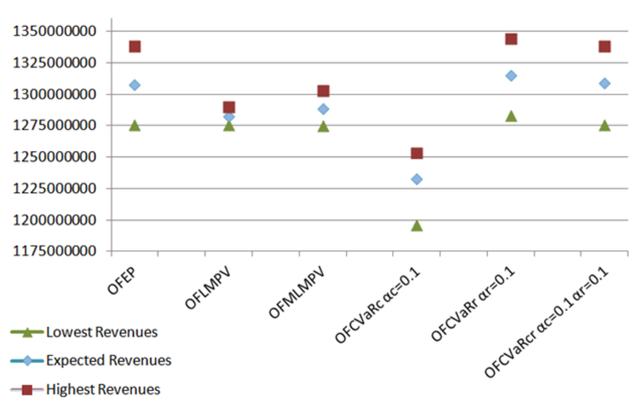

Figure 3. Lowest, expected, and highest revenues.

functions. The lowest and highest values are obtained for the most favorable and critical scenarios considering that the initial design of the network is determined at time t_0 and the structure network can be adapted at time period t_1.

As can be seen in Figures 2–4, the solution achieved with OFEP presents the highest difference between the extreme values of the costs, revenues, and profits. Considering all the utility functions, it can be seen that the solution obtained with OFCVaRcr is a compromise solution, which allows better

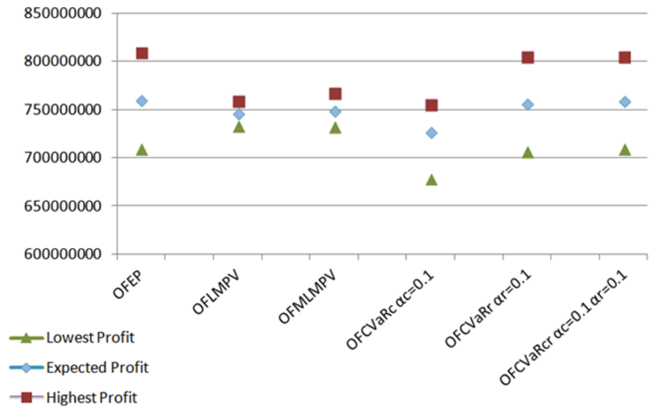

Figure 4. Lowest, expected, and highest profits.

expected revenues than the results achieved with all the objective functions, with the exception of OFCVaRr. Nevertheless, considering the lowest and expected profits, the solution achieved with OFCVaRcr is better than the one obtained with OFCVaRr. In addition, while OFCVaRcr presents expected costs greater than those obtained with OFEP (0.42%), expected revenues are 0.13% greater than those achieved with OFEP. On the other hand, it is important to remark that the solution obtained with OFCVaRc presents the smallest values for lowest, expected, and highest magnitudes of costs, revenues, and profits.

Figure 5 shows the costs connected with the network structures. While the rhombuses represent the costs associated

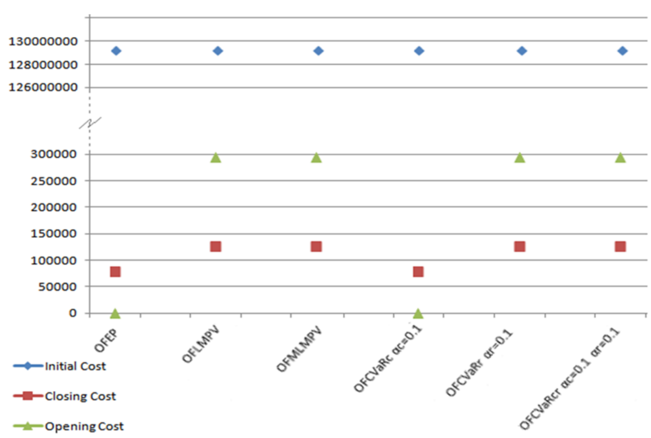

Figure 5. Costs for initial, closing, and opening network structures.

with the initial structure of the supply chain, triangles and squares correspond to the costs related to the entities that are opened and closed after starting the network operation. Thus, triangles and squares correspond to the different cost levels associated with the resulting network structure for time period t_1. While the initial structure is equal for all utility functions, performance measures associated with risk (with the exception of OFCVaRc) perform more structural changes than OFEP in order to deal with the alterations of the market conditions. For example, while OFEP and OFCVaRc decrease the number of entities eliminating a repairing center during the time period t_1, OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr change the structure of the supply chain opening and closing entities.

Table 2 lists the network structures for the different objective functions. It illustrates the initial network structure (root node

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Table 2. Network Structures

Entity			s1	s2	s3	f1	f2	f3	w1	w2	dc1	dc2	cc1	cc2	cc3	rc1	rc2	d1	d2	dp1	dp2	fd1	fd2
OFEP OFCVaRc	n_0	t_0	*	*	*	*		*	*			*	*	*	*	*	*	*	*	*			*
	n_4	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*	*			*
	n_5	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*	*			*
	n_6	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*	*			*
OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr	n_0	t_0	*	*	*	*		*	*			*	*	*	*	*	*	*	*	*			*
	n_4	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*	*			*
	n_5	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*		*		*
	n_6	t_1	*	*	*	*		*	*			*	*	*	*	*		*	*		*		*

of the scenarios tree at time period t_0), which is common for all scenarios, and the structure that can be adopted by the supply chain at time period t_1 depending on the occurrence of certain events in the nodes. As can be seen from Table 2, the objective functions OFEP and OFCVaRc lead to an initial network structure with 16 entities, which is contracted during the planning of the supply chain. Nevertheless, the solutions obtained using OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr follow a different behavior. They start the network structure with 16 entities, and then, the number of entities is preserved considering that when an entity is open, another is closed. When comparing the structure obtained with OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr, with the one achieved with OFEP and OFCVaRc, it can be observed that the inclusion of decomposition center 2 (dp2) and the removal of decomposition center 1 (dp1), at time period t_1 of nodes n_5 and n_6, are key aspects to obtain a more reliable solution. The use of dp2 allows increasing or maintaining the flow of products that are sent to plants and suppliers, as the minimal storage capacity of dp2 is less than the capacity of dp1. Therefore, it is important to note that the objective functions OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr take greater advantage of the potential adjustments in the structure of the supply chain than the other two objective functions.

6.2. Sensitivity Analysis Study. First, a sensitivity analysis study is conducted considering the results obtained with the performance measures where the CVaR concept is applied to costs, revenues, and both simultaneously (OFCVaRc, OFCVaRr, and OFCVaRcr). The study aims to show the importance of considering at the same time the application of the CVaR concept to costs and revenues. Three cases for λ (0.5, 1, 2) and three cases for αc and αr (0.1, 0.5, 0.9) are considered. While a small value of α, for example 0.1, implies a large confidence level of 0.9, a big value of α, for example 0.9, denotes a reduced confidence level of 0.1.

Figures 6 and 7 illustrate the results obtained considering different utility functions and values of αc and αr. It can be seen from Figure 6 that the utility function OFCVaRc, which is centered in reducing the likelihood that the design and planning of a given CLSC incur large costs for different confidence intervals, shows the smallest values for the highest, expected, and lowest costs. Similarly, OFCVaRc presents the smallest values for the highest, expected, and lowest revenues. Considering the different values of αc for OFCVaRc, it can be observed that $\alpha c = 0.1$ is associated with the widest confidence interval, which generates a largest search space that allows selection of a solution with the best expected costs, but with extreme values further separated from the expected value. On the other hand, for the other two cases ($\alpha c = 0.5$ and 0.9), it should be mentioned that their confidence intervals generate smaller search spaces than the case with $\alpha c = 0.1$. Thus, αc = 0.5 and 0.9 lead to solutions with worse expected costs, but with extreme values for costs and revenues more adjusted to the expected values. Importantly, from the point of view of the objective function considered, the main quantity to be taken into account is the difference between the expected costs and the worst costs that occur in each case. While the difference is zero for $\alpha c = 0.5$ and 0.9, the discrepancy represents 3.1% of the expected costs for $\alpha c = 0.1$. Since OFCVaRc takes into account only the risk associated with the costs, Figure 7 shows the values indirectly obtained for the highest, expected, and lowest revenues when using OFCVaRc.

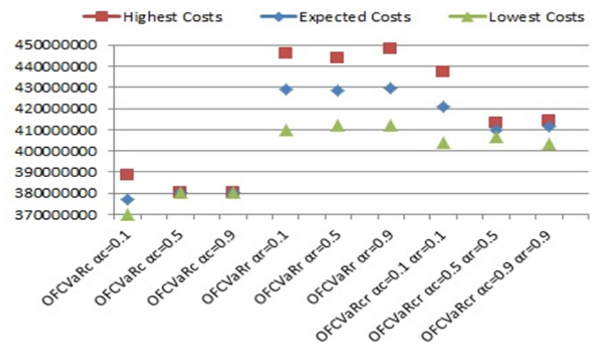

Figure 6. Lowest, expected, and highest costs for different values of αc and αr.

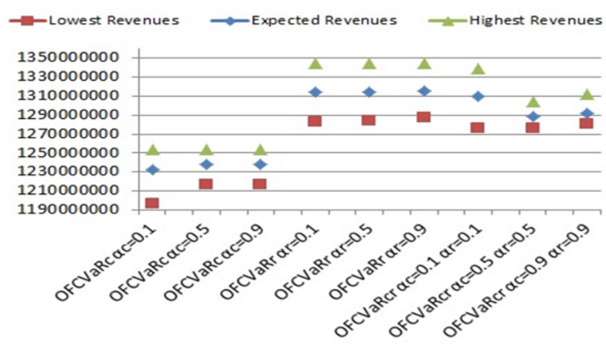

Figure 7. Lowest, expected, and highest revenues for different values of αc and αr.

OFCVaRr is used to reduce the likelihood that the design and planning of a given CLSC incur a large reduction of revenues. The highest, expected, and lowest revenues, when using OFCVaRr, are shown in Figure 7 and the indirect values for highest, expected, and lowest costs are illustrated in Figure 6. When OFCVaRr is taken into account, $\alpha r = 0.1$ is associated with the largest search space that allows selection of a solution with a wider range between the highest and lowest revenues than the cases with $\alpha r = 0.5$ and 0.9. Nevertheless, the solutions do not significantly changes due to the parametric character-

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Ind. Eng. Chem. Res. 2016, 55, 6236−6249

istics of the problem. While the expected revenues remain almost the same for the three values of αr, the differences between the expected returns and the lowest revenues for αr = 0.5 and 0.9 are about 96% and 89% of the difference obtained with αr = 0.1.

Finally, the results obtained with OFCVaRcr also can be seen in Figures 6 and 7. This utility function pursues a trade-off between the negative effects on the overall network performance due to possible increase of costs and the decline of revenues. When considering $\alpha c = \alpha r$ = 0.1 in OFCVaRcr, the expected costs and revenues are the highest of the three cases ($\alpha c = \alpha r$ = 0.1, 0.5, and 0.9). Moreover, the difference between the expected costs and the highest costs, as well as the difference between the expected revenues and the lowest revenues for $\alpha c = \alpha r$ = 0.1, are also greater than in the other cases.

Considering the expected profit for the different utility functions (see Figure 8), it can be seen that OFCVaRcr with αc = αr = 0.1 obtains the best expected profits of all cases. Moreover, taking into account the solutions obtained with αc = αr = 0.9, it is important to note that the expected profit for OFCVaRcr is 2.9% higher than the solution obtained with OFCVaRc and only 0.7% smaller than the result achieved with OFCVaRr.

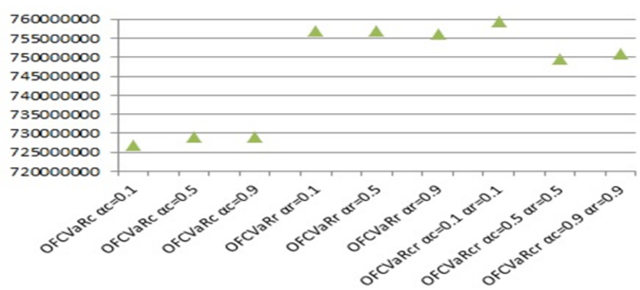

Figure 8. Expected profits for different values of αc and αr.

The relevance of the risk criterion increases with respect to the expected terms of the objective function when the value of λ is increased. Figures 9 and 10 show the results obtained with OFCVaRcr when $\alpha c = \alpha r$ = 0.5 and with λ from 0.5 to 1.5. As can be seen from Figures 9 and 10, while the highest and expected costs and revenues follow a decreasing tendency when λ increases, the lowest costs and revenues almost do not change. Therefore, in both cases, costs and revenues, the difference between the highest and lowest values decreases when λ increases, due to mainly to the decreasing tendency of the highest values.

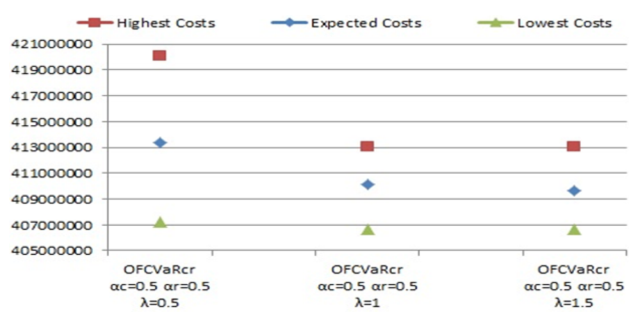

Figure 9. Lowest, expected, and highest costs for different values of λ.

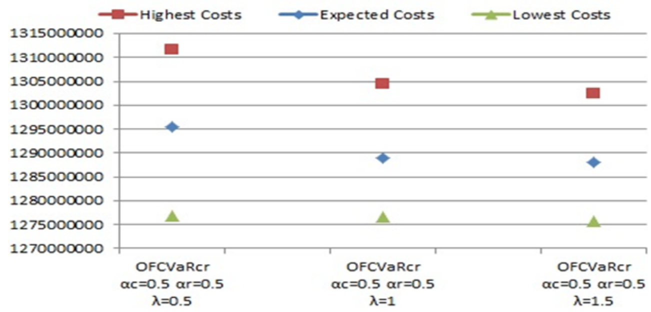

Figure 10. Lowest, expected, and highest revenues for different values of λ.

Figure 11 illustrates the expected profits obtained with different values of λ. The expected profits decrease as the parameter λ goes from 0.5 to 1.5. It is worth remarking that the cases with parameters λ = 1 and 1.5 show an important decreasing of the expected profit with respect to the case with λ = 0.5.

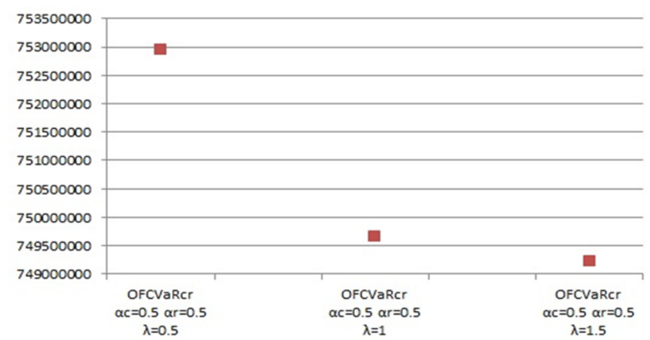

Figure 11. Expected profits for different values of λ.

Finally, in order to compare the effectiveness of performance metrics, OFLMPV, OFMLMPV, and OFCVaRcr, to obtain solutions with less risk without a large decrease of expected profits, Figure 12 illustrates the expected profit versus the risk quantification performed in each objective function (terms LMPV, MLMPV, and CVaRcr) while different values of λ are considered (λ from 0.5 to 1.5). Squares, triangles, and rhombuses represent the results obtained with OFCVaRcr, OFLMPV, and OFMLMPV, respectively. From Figure 12, it can be seen that while the value of λ increases, the expected profits obtained with OFLMPV decrease faster than the expected profits achieved with OFMLMPV and OFCVaRcr. On the other hand, the expected profits obtained with OFCVaRcr are greater than the expected profits achieved with OFLMPV and OFMLMPV for λ = 1 and 1.5.

As conclusions, the sensitivity analysis leads to some interesting points:

- Given the different values for the confidence levels, it can be observed that a confidence level equal to 0.1 is associated with a wide confidence interval, which generates large search spaces allowing select solutions with high quality expected values, but with extreme magnitudes separated from the expected values.
- Given the characteristics of the problem addressed and considering any objective function, it should be noted that a change of the confidence level from 0.5 to 0.9 does not have much impact on the solutions. In addition,

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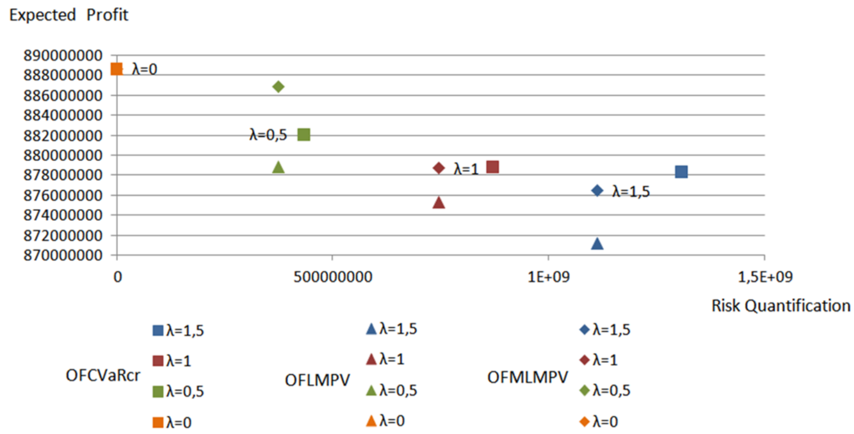

Figure 12. Expected profits vs Risk Quantification for different values of λ.

when OFCVaRr is taken into account, the confidence level variations do not generate significant changes of the solutions.

- Taking into account the solutions obtained with OFCVaRr and OFCVaRcr, the performance of OFCVaRc is unsatisfactory in values of expected profits.
- OFCVaRcr gets trade-off solutions between costs and revenues, which are of good quality considering as reference the expected profit. In addition, taking into account the expected profit, the solutions obtained with OFCVaRcr are close to the solutions obtained using OFCVaRr.
- Considering the effects of λ on the objective function OFCVaRcr, it should be noted that when λ is increased, the solutions have more risk-averse behavior since the relevance of the risk criterion increases with respect to expected terms of the objective function.
- Given the characteristics of the problem addressed, when the parameter λ (on the objective function OFCVaRcr) goes from 1 to 1.5, the solutions are similar.
- Comparing the effectiveness of performance metrics OFLMPV, OFMLMPV, and OFCVaRcr, it is important to note that when the parameter λ is equal to 1 and 1.5, OFCVaRcr obtains solutions with less risk and better expected profits than OFLMPV and OFMLMPV.

7. CONCLUDING REMARKS

A comprehensive risk-averse stochastic framework is presented in this paper in order to deal with the design and planning problem of multiperiod, multiproduct closed-loop supply chains with supply and customer demands as uncertain parameters. The approach is the type multistage that considers adjustments in the supply chain structure during the planning horizon. Thus, the formulation adopts design decisions of the first period as the variables that must be determined before the resolution of the underlying uncertainty, and the design variables corresponding to the next time periods as well as the decisions related to production, transportation, distribution, and storage are variables subject to adjustment when specific realizations of uncertain parameters occur. In addition, the stochastic approach addresses a problem of a generic multiperiod multiproduct CLSC with a general network structure of ten types of entities, transport capacity, salvage grade of returned products, CO_2 emissions of the transport system, as well as minimum and maximum storage and processing capacity limits for network entities.

The objective criterion is to maximize the supply chain profits considering risk measures to deal with the volatile conditions of the market. Five objective functions that include risk-averse criteria are considered and their results are compared. Thus, results show some interesting points. OFCVaRcr can be seen as a conceptually more advanced objective function than OFCVaRr and OFCVaRc because the explicit consideration of the risk of costs and revenues allows the decision maker to choose the relative importance and the desired confidence level for each magnitude. Another important advantage of OFCVaRcr is that optimal solutions are reached in comparable CPU time compared to those obtained by other objective functions considering the risk (for example for the modified linear measure of the profits variability: OFMLMPV). In addition, the expected profits obtained with OFCVaRcr are greater than the values achieved with OFLMPV and OFMLMPV. Moreover, when the solutions obtained with OFCVaRcr are compared with the results achieved with the utility functions that consider the effects of risk of costs and revenues separately, it is noted that the former solutions obtain trade-off results with suitable levels of expected profits and extreme values for costs and revenues. Considering the network structure, the objective functions OFLMPV, OFMLMPV, OFCVaRr, and OFCVaRcr take more advantage of the potential adjustments in the structure of the supply chain than OFEP and OFCVaRc.

As future work, two main points can be stated. An area for further investigation is to enhance the stochastic model to deal with a more precise representation of the distribution functions of the uncertain parameters. On the other hand, alternative solution methods are to be tested in order to improve the exploration of the solution space and reduce the computational effort.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.iecr.5b03647.

Model nomenclature and data used in the example problem (PDF)

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Notes

The authors declare no competing financial interest.

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■ REFERENCES

(1) Cardoso, S.; Barbosa-Póvoa, A. P.; Relvas, S. Design and Planning of Supply Chains with Integration of Reverse Logistics Activities under Demand Uncertainty. *Eur. J. Oper. Res.* **2013**, *226* (3), 436−451.

(2) Sahebi, H.; Nickel, S.; Ashayeri, J. Environmentally Conscious Design of Upstream Crude Oil Supply Chain. *Ind. Eng. Chem. Res.* **2014**, *53* (28), 11501−11511.

(3) Mota, B.; Gomes, I.; Carvalho, A.; Barbosa-Póvoa, A. P. Towards supply chain sustainability: economic, environmental and social design and planning. *J. Cleaner Prod.* **2015**, *105*, 14.

(4) Guide, V. D. R.; Van Wassenhove, L. N. The evolution of closed-loop supply chain research. *Oper. Res.* **2009**, *57*, 10−18.

(5) Ahmed, S.; Sahinidis, N. V. Robust Process Planning under Uncertainty. *Ind. Eng. Chem. Res.* **1998**, *37* (5), 1883−1892.

(6) Papageorgiou, L. G. Supply chain optimization for the process industries: Advances and opportunities. Comp. *Comput. Chem. Eng.* **2009**, *33* (12), 1931−1938.

(7) Noyan, N. Risk-averse Two-stage Stochastic Programming with an Application to Disaster Management. *Comp. & Oper. Res.* **2012**, *39*, 541−559.

(8) Krokhmal, P.; Palmquist, J.; Uryasev, S. Portfolio Optimization with Conditional Value-at-risk Objective and Constraints. *J. Risk* **2002**, *4* (2), 99−114.

(9) Miller, N.; Ruszczynski, A. Risk-averse Two-stage Stochastic Linear Programming: Modeling and Decomposition. *Oper. Res.* **2011**, *59* (1), 125−132.

(10) Ruszczynski, A.; Shapiro, A. Optimization of Risk Measures. In *Probabilistic and Randomized Methods for Design under Uncertainty*; Calafiore, G., Dabbene, F., Eds,; Springer-Verlag: London, 2006; pp 119−157.

(11) Ahmed, S. Convexity and Decomposition of Mean-risk Stochastic Programs. *Math. Program.* **2006**, *106* (3), 433−446.

(12) Soleimani, H.; Mirmehdi, S.; Govindan, K. Incorporating risk measures in closed-loop supply chain network design. *Int. J. Prod. Res.* **2014**, *52* (6), 1843−1867.

(13) Carneiro, M. C.; Ribas, G. P.; Hamacher, S. Risk Management in the Oil Supply Chain: A CVaR Approach. *Ind. Eng. Chem. Res.* **2010**, *49* (7), 3286−3294.

(14) Verderame, P. M.; Floudas, C. A. Operational Planning of Large-Scale Industrial Batch Plants under Demand Due Date and Amount Uncertainty: II. Conditional Value-at-Risk Framework. *Ind. Eng. Chem. Res.* **2010**, *49* (1), 260−275.

(15) McNeil, A. J.; Frey, R.; Embrechts, P.. *Quantitative Risk Management: Concepts, Techniques, and Tools*; Princeton University Press: Princeton, NJ, 2010.

(16) Najafi, A. A.; Mushakhian, S. Multi-stage stochastic mean−semivariance−CVaR portfolio optimization under transaction costs. *Appl. Math. Comp.* **2015**, *256*, 445−458.

(17) Rockafellar, R. T.; Uryasev, S. Optimization of Conditional Value-At-Risk. *J. Risk* **2000**, *2* (3), 21−41.

(18) Rockafellar, R. T.; Uryasev, S. Conditional Value-at-risk for General Loss Distributions. *Journal of Banking and Finance* **2002**, *26*, 1443−1471.

(19) Souza, G. C. Closed-Loop Supply Chains: A Critical Review, and Future Research. *Decision sciences Journal* **2013**, *44* (1), 7−38.

(20) Govindan, K.; Soleimani, H.; Kannan, D. Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *Eur. J. Oper. Res.* **2015**, *240* (3), 603−626.

(21) Salema, I.; Barbosa-Póvoa, A. P.; Novais, A. Q. An Optimization Model for the Design for a Capacitated Multi-product Reverse Logistics Network with Uncertainty. *Eur. J. Oper. Res.* **2007**, *179*, 1063−1077.

(22) Francas, D.; Minner, S. Manufacturing Network Configuration in Supply Chains with Product Recovery. *Omega* **2009**, *37* (4), 757−769.

(23) Pishvaee, M. S.; Jolai, F.; Razmi, J. A stochastic optimization model for integrated forward/reverse logistics network design. *J. Manuf. Syst.* **2009**, *28* (4), 107−114.

(24) Lee, D.; Dong, M. Dynamic network design for reverse logistics operations under uncertainty. *Transportation Transp. Res. Part E: Logist. Transp. Rev.* **2009**, *45* (1), 61−71.

(25) Pishvaee, M. S.; Rabbani, M.; Torabi, S. A. A robust optimization approach to closed-loop supply chain network design under uncertainty. *Appl. Math. Modell.* **2011**, *35* (2), 637−649.

(26) Zeballos, L. J.; Gomes, M.; Barbosa-Povoa, A. P.; Novais, A. Q. Addressing the uncertain quality and quantity of returns in closed-loop supply chains. *Comput. Chem. Eng.* **2012**, *47*, 237−247.

(27) Amin, S. H.; Zhang, G. A multi-objective facility location model for closed-loop supply chain network under uncertain demand and return. *Appl. Math. Modell.* **2013**, *37* (6), 4165−4176.

(28) Zeballos, L. J.; Mendez, C. A.; Barbosa-Povoa, A. P.; Novais, A. Q. Multi-period design and planning of closed-loop supply chains with uncertain supply and demand. Comp. *Comput. Chem. Eng.* **2014**, *66* (4), 151−164.

(29) Khatami, M.; Mahootchi, M.; Farahani, R. Z. Benders' decomposition for concurrent redesign of forward and closed-loop supply chain network with demand and return uncertainties. *Transp. Res. Part E: Logist. Transp. Rev.* **2015**, *79*, 1−21.

(30) Ben-Tal, A.; Nemirovski, A. Robust solutions to uncertain linear programs. *Operations Research Letters* **1999**, *25* (1), 1−13.

(31) Gebreslassie, B. H.; Yao, Y.; You, F. Design under uncertainty of hydrocarbon biorefinery supply chains: Multiobjective stochastic programming models, decomposition algorithm, and a Comparison between CVaR and downside risk. *AIChE J.* **2012**, *58*, 2155−2179.

(32) Cardoso, S.; Barbosa-Póvoa, A. P.; Relvas, S. Integrating Financial Risk Measures into the Design and Planning of Closed-loop Supply Chains Comp. *Comput. Chem. Eng.* **2016**, *85*, 105−123.

(33) Subulan, K.; Baykasoğlu, A.; Özsoydan, F. B.; Taşan, A. S.; Selim, H. A case-oriented approach to a lead/acid battery closed-loop supply chain network design under risk and uncertainty. *J. Manuf. Syst.* **2015**, *37*, 340.

(34) Yu, C.; Li, H. A robust optimization approach for stochastic logistic problems. *Int. J. Prod. Econ.* **2000**, *64*, 385−397.

(35) Wagner, H. *Principles of Operations Research*; Prentice-Hall: NJ, 1975.

(36) Paksoy, T.; Bektas, T.; Özceylan, E. Operational and environmental performance measures in a multi-product closed-loop supply chain. *Transp. Res. Part E: Logist. Transp. Rev.* **2011**, *47* (4), 532−546.

(37) Dupacova, J.; Growe-Kuska, N.; Romisch, W. Scenario reduction in stochastic programming: An approach using probability metrics. *Math. Program. Ser. A* **2003**, *95*, 493−511.

(38) Heitsch, H.; Romisch, W. Scenario reduction algorithms in stochastic programming. *Comp. Opt. Applic.* **2003**, *24*, 187−206.

(39) Growe-Kuska, N.; Heitsch, H.; Romisch, W. Scenario reduction and scenario tree construction for power management problems. *IEEE Bologna Power Tech Proceedings*; Borghetti, A., Nucci, C. A., Paolone, M., Eds.; IEEE: Bologna, 2003; pp 2−4.

(40) GAMS/SCENRED Documentation, available from www.gams.com/help/index.jsp?topic=%2Fgams.doc%2Ftools%2Fscenred%2Findex.html, 2013.